Modelling Electoral Landslides: United States Presidential Elections, 1992-2016

Much has been written about the polarization of the American electorate and its reflection in its legislatures, but less about its spatial polarization, which Bishop has argued has taken place in parallel with the ideological and behavioural polarization. The extent of that polarization can be assessed, he argues, by identifying the number of 'landslide counties, those won at presidential elections by margins of 20 percentage points or more. This paper looks at the change in the number and extent of those landslide counties over the period 1992-2016, relative to both the location of the counties and their population composition, using multilevel modelling. It shows that a county's population composition was a major determinant of whether it returned a landslide for either party's candidate at any election – with a clear change in direction over the period for counties according to their level of affluence – but this was by no means the sole determinant. Holding constant those variations there were additional geographies that were more place- than people-specific.

Keywords: United States; presidential elections; spatial polarization; counties; landslides

The ideological polarization of the American population and its elected representatives has been the source of much recent debate – as in Campbell's (2016, 1) recent conclusion that 'America is polarized. Our political parties are highly polarized and the American electorate is highly polarized. … Political divisions in American politics are now deep and real'. That polarization is not as extreme as in some countries: it distinguishes liberals from conservatives (with a substantial moderate minority between them), not totalitarians from anarchists. The core American values remain – peace and prosperity, equal opportunities etc. – but liberals and conservatives differ significantly on the means to those ends, and the variations in their ideological commitments to those means have become deeper in recent decades.

Linked to that work on greater ideological polarization among the American electorate and its representatives are parallel arguments about spatial polarization of the electorate. Over recent decades, it is argued, the country has become geographically more polarized, with more areas increasingly dominated by support for either the Democratic or the Republican candidate for the presidency. A major figure in this argument has been a journalist, Bill Bishop, whose 2008 book with Robert Cushing – reprinted and updated in 2009 – on *The Big Sort* had an opening chapter entitled 'The age of political segregation'. After the traumatic events of 1968, he claimed, the country became increasingly polarized as similar people concentrated even more into particular areas, hence (Bishop, 2009, 40):

> The country may be more diverse than ever coast to coast. But look around: our own streets are filled with people who live alike, think alike, and vote alike. This social transformation didn't happen by accident. We have built a country where everyone can choose the neighborhood (and church and news shows) most compatible with his or her lifestyle and beliefs. And we are living with the consequences of this segregation by way of life: pockets of like-minded citizens that have become so identically inbred that we don't know, can't understand and can barely conceive of "those people" who live just a few miles away.

Selective migration, according to this hypothesis, is leading to a more segregated country, a situation exacerbated recently by gerrymandering which, by refusing to find egregious gerrymanders unconstitutional, a Supreme Court 2006 decision has encouraged (McGann et al., 2016; Daley, 2016). This creates more politically safe districts where parties are increasingly likely to select ideologically relatively extreme candidates in their primaries, so contributing to greater ideological polarization in the House of Representatives.

Most of Bishop's book advances his argument through qualitative data and case studies, but he claims that Cushing sustained the argument by testing it using all of the 'several ways to measure segregation' (p.9) devised by demographers. His conclusion was further sustained by use of more recently-developed measures that evaluate the degree of segregation at three spatial scales (Johnston et al., 2016). Since 1992, the pattern of voting at Presidential elections has become increasingly more polarized across the nine divisions deployed by the Bureau of the Census for much statistical presentation; additionally, it has become more polarized across the states within those divisions, as well as across the counties (or county-equivalents) within states.

With that statistical basis for his argument in the background, Bishop (p.9) argued that the

> … simplest way to describe this political big sort was to look across time at the proportion of voters who lived in landslide counties – counties where one party won by 20 percentage points or more.

The number of such counties, and the share of the voting population living there, varied across the elections that he studied – from 1948 to 2004 (with a brief update for 2008). In what he terms uncompetitive elections – 'when the entire country seemed to side with one party or the other' – as many as 55 (1984), 59 (1972) and 64 (1964) per cent of the voting population lived in counties where the winning candidate for the presidency from the two main parties (Republican and Democratic) led his opponent by 20 percentage points or more. In competitive elections, when the winning candidate's margin was less than 10 points nationally, that percentage was only 27 in 1974, but by 2004 it had increased to 48: nearly half of those who turned out to vote lived in counties won by a landslide, creating what he termed a 'fractured, discordant country' (p.15).

Bishop's argument has come under some criticism, but not outright rejection. Prior to the appearance of his book, Fiorina and Abrams (2008), for example, referred to some of his journalism which presaged his later argument that 'most Americans are living in communities that are becoming politically more homogeneous … and that grouping of like-minded people is feeding the nation's rancorous and partisan politics'.[1] Reviewing the small literature on geographical polarization, they note that most of it relates to election returns rather than measures of individuals' partisan positions and that little of it provides strong evidence of any polarization trend. (This includes an analysis by Glaeser and Ward, 2006, which showed little more than trendless fluctuation over the period 1860-1976, but from 1976 to 2004 it showed a steady increase, with their polarization measure more than doubling over the period.) Further, they conclude that election outcomes are 'not measures of voter positions and cannot be used as indicators of such' (Fiorina and Abrams, 2008, 577), implicitly arguing that even if analysis of election returns shows greater polarization this cannot be used to imply that people with similar views are congregating together. In a later paper, relating directly to Bishop's (2009) book, they rehearse similar arguments (Abrams and Fiorina, 2012). Their conclusion is not a complete rejection:

> There is no evidence that a geographic partisan "big sort" like that described by Bishop is ongoing, and even if it were, its effects would be far less important than Bishop and those who support his thesis fear. (Abrams and Fiorina, 2012, 208).

They accept – as do Campbell (2016) and many others – that the American electorate is becoming more polarized but 'however important or troubling … [that] may be, *such trends are independent of geographic political sorting*' (Abrams and Fiorina, 2012, 208; their emphasis)

ELECTORAL LANDSLIDES IN AMERICAN COUNTIES

[1] The quotation, on p. 576 of Fiorina and Abrams' (2008) paper is taken from B. Bishop, 'The cost of political uniformity' which appeared in the *Austin American Statesman* on 8 April 2004.

Abrams and Fiorina's overall case is that:

> Do the preceding analyses prove that political residential segregation is not occurring? No. That is not our position. We are simply pointing out that Bishop's sweeping argument about geographical political sorting has no empirical foundation. (Abrams and Fiorina, 2012, 206).

They are sceptical that geographical polarization is occurring (has occurred over recent presidential elections): their 2008 conclusion was that '… geographical polarization – the hypothesized tendency of like-minded people to cluster together – remains an open question' (Fiorina and Abrams, 2008, 563). Even if it is, however, they reject Bishop's argument that this is because people with similar ideological positions are increasingly segregating themselves from those with other positions. The two are separate. Bishop makes strong empirical claims regarding the first – geographical polarization. If those can be sustained through rigorous analysis, they the raise important questions regarding the sorting processes that are going on and their implications for other forms of polarization. This paper is concerned entirely with that first set of claims, with a rigorous statistical analysis of the changing geography of landslide counties over the period 1992-2016.

Table 1 shows the number of landslide counties for each of the two main parties, plus the number that were not won by a landslide majority, at each of the presidential elections since 1992 covering counties in all states except Alaska; the District of Columbia is also excluded.[2] Over that twenty-four-year period there have been three major changes: the number of counties won by a landslide by the Republican candidate increased almost threefold, from 588 to 2,217; the number won by the Democratic party candidate almost halved; and the number of counties not won by a landslide also declined, to less than one-third of its 1992 total. There was a slight hiatus in those trends in 2008 – Barack Obama's first victory – but they were reinstated again in 2012. At the county scale, the country has become much more polarized: in 1992, 64 per cent of all counties were won by less than the landslide 20 per cent margin, whereas in 2016 that was the case in only 21 per cent. In terms of the number of counties that greater polarization strongly favours the Republicans: their candidate won 53 per cent of the landslide counties in 1992, but 91 per cent of them in 2016.

These paper looks at those trends in the number and location of landslide counties in more detail. It follows Bishop in defining them – the counties where one party predominated at a particular election – as those won by more than twenty points as a share of the total number of votes won there by the Democratic and Republican party candidates, thereby removing from the calculations all 'third party' candidates. Any choice of a threshold between landslide and non-landslide counties is necessarily arbitrary, but 20 per cent is useful because very few counties won by that margin by one party are later won by the opposing party. For example, of the 588 Republican landslide counties in 1992, none were won by the Democratic candidate in 1996, and of the 526 Democratic landslide counties at the first date only one was won by the Republican candidate four years later. At subsequent elections, almost no counties that returned a Republican landslide then delivered a Democratic victory at the following contest. Indeed, of the 588 Republican landslide counties in 1992, only seven returned a majority for the Democratic party's candidate 24 years later in 2016. A very similar pattern applies to Democratic landslide counties also, with one exception: of the 544 counties returning a Democratic landslide in 1996, 95 provided a majority for the Republican candidate in 2000. Most of those counties were in southern states, notably Arkansas, where Bill Clinton won by a landslide in 17 of his home state counties that gave a majority to George W. Bush in 2000, and neighbouring states such as Kentucky, Louisiana, and Oklahoma.

[2] There is no consistency in the county-equivalent subdivisions of Alaska over the period: the District of Columbia has no subdivisions. The data used here are a bespoke set showing presidential voting for a consistent set of counties for the period 1992-2016 inclusive, constructed by Clark Archer, Fred Shelley and Bob Watrell from official state sources. We are grateful to them for allowing us to use this.

Where are those 'landslide counties', and what are the characteristics of their populations? Initial cartographic analysis identifies very clear patterns. Figure 1 shows the counties according to the number of landslides delivered for each party across all seven elections. The core area for Republican landslides, with six or seven landslides, covers many of the states of the Great Plains and the Mountains, and this expanded south into much of Texas (where Republican candidate in 2000 and 2004 – George W. Bush – had been governor) and westward into inland California, Oregon and Washington. There was also considerable expansion of the areas of Republican hegemony to the east of the Mississippi-Missouri rivers, mainly to the west of the Appalachians, but in substantial parts of the Upper Midwest (Iowa, Michigan, Minnesota and Wisconsin) few counties delivered more than one landslide most of them in 2016. Counties that delivered regular landslide victories to the Democratic party candidates were increasingly concentrated on the seaboards, plus along the border with Mexico, in some inland metropolitan areas (such as Chicago), parts of Arizona and New Mexico (which have large Hispanic populations) and in parts of the 'Black Belt' along the lower Mississippi. But the latter was a major area of change: in Arkansas Bill Clinton won by a landslide in 45 of his home state's 75 counties in 1992 and 48 in 1996; Al Gore won just eight by a landslide there in 2000, and Hillary Clinton only two in 2016. No Arkansas county delivered a landslide majority to the Republican candidate in 1992; 60 did in 2016.

As one candidate expressed it, by 2016 'Purple America has all but disappeared'; most of the country's map by county was either red – safe Republican – or blue – safe Democrat. And because there were many more red than blue counties the implication was that not only did an ever-decreasing share of the electorate live in counties won by less than 20 percentage point margins but the same was the case with regard to Democratic voters. That was not fully the case, however. The number of voters living in counties without landslide victories remained fairly stable over the period (Table 2), although with the growth of the electorate the percentage declined – from 61 in 1992 to 39 in 2016. In 1992, 73 per cent of voters living in a landslide county were in one where the Democratic candidate triumphed, but by 2016 that had been reduced to 50 per cent. The number of voters living in counties that delivered Republican landslides more than quadrupled over the period, at the end of which there was virtual equality between the two parties. There were many more Republican than Democrat landslide counties in 2016, therefore, but not many more voters living in the former than the latter: the mean number of voters in a Republican landslide county then was 17,281, compared to 169,872 in a Democrat landslide county; the mean for counties with no landslide for either party was 79,938.

Apart from their size, how did the different types of county vary in terms of their population characteristics? Bishop suggested that the observed polarization resulted from greater clustering of population groups according to income, educational qualifications, religious affiliation and observance, ethnicity, immigrant status, and household structure. Census data for c.2010 were assembled by county for a range of variables matching those; they refer to the end of the period considered and so we anticipated that landslide counties then would be those towards the extremes of the various criteria – Democratic landslides in counties with large Black populations, for example.

Table 3 shows that counties that delivered Democrat landslides in 2016 had many more adults with degrees than those that delivered Republican landslides; they also had many more Blacks and Hispanics in their populations and, as a consequence, many fewer non-Hispanic Whites. Many of those census variables have similar geographies (i.e. are inter-correlated), however, and so a clearer view of the differences is given by combining the groups of inter-correlated variables through a principal components factor analysis. Three (direct-oblimin rotated) factors were extracted (Table 4): the first links areas with high levels of persons living in poverty, of unemployed persons, and of Blacks with low percentages of non-Hispanic Whites – and vice versa; the second links family incomes with the percentage of adults having degrees; and the third identifies a continuum of counties according to their percentage of Hispanics. The mean factor scores on those three dimensions are given at the foot of Table 3, with clear contrasts between counties according to whether they returned a landslide in 2016, and if so for which party. A large positive mean score (1.24) on the first factor shows that counties with Democratic landslides had many more Blacks and families in poverty than those that delivered Republican landslides (a mean score of -0.28). There were also substantial differences between the Democrat and Republican landslide counties on the second and third factors: the means of 0.74 and -0.24 respectively on the second indicate that democrat-landslide counties had many more degree-holders and high-income households than those returning Republican landslides. Finally, means of -1.10 and 0.18 respectively indicate that the Democrat landslide counties had more Hispanics than average (the loading for this variable is negative: Table 4) whereas the Republican landslide counties had above-average percentages of non-Hispanic Whites.

MODELLING

Counties that delivered landslides for one or other of the two parties' candidates were concentrated in particular states, therefore, and also had characteristic socio-demographic and socio-economic profiles. But how important were those two apparent determinants of landslide delivery, and did their relative impact differ over time? To address that question, we have fitted a series of multi-level multinomial logistic models, with years (seven, 1992-2016) nested within counties (3,077) nested within states (49). In these, counties with either a Republican or Democratic landslide are contrasted with those where neither party gained a landslide victory at the relevant election. Five models were fitted (details are given in the Appendix); each, shown by the reduction in the DIC measure (a complexity-penalized badness- of-fit measure), was a substantial improvement on the previous one.

The five models address the following questions:

1. Were there significant national trends in the number of counties delivering landslide victories to either the Republican or the Democratic rather than having no landslide over the seven elections?
2. Within those trends, were there significant variations in the trajectories between states and counties?
3. Were the trajectories related to the county population characteristics with, for example, certain types of county more likely than others to have Democratic landslides, and, if so, were there still between-state and between-county variations not accounted for by the county population characteristics?
4. Did the impact of a county's population characteristics on its probability of delivering a landslide for one or other of the parties change over time? And
5. Did the relationships between the probability of a county delivering a landslide for one or other of the parties and their population characteristics differ over time?

Model 1: Time Variant Only

In the first model the only predictor is year (Table 5), expressed as the year of the election centred on 1992, with the model estimating the probability (actually modelled as a logit) of the county delivering either a Republican or a Democratic landslide, contrasted with having no landslide, in each year. In the fixed part which gives the general trend, the coefficients for year are statistically significant at the 0.001 level or better, showing that the logits of the outcomes have changed over time. The logits are converted to probabilities and the modelled trends by year for the mean county in the mean state (the so-called population average results Jones and Subramanian, 2017b) are shown in Figure 2. This indicates a very substantial increase in the probability of a Republican landslide and a substantial decrease in the probability of a county not delivering a landslide. For Democrat landslides, there is a substantial decline from an already low base.

In the random part of the model, the variances summarize the differences between states and between counties within states around the overall trends associated with year. In this initial model, the variances represent the differences over the entire period with the greatest variance at the state level for Republicans and for Democrats at the county level. All the variances are large and far away from the zero value of no segregation – there is considerable polarization for both parties at both state and county level. Figure 3 shows how states differ and what the variance terms are summarizing. The horizontal axis shows the differential logit (i.e. the log-odds of the probability) for a county within a state delivering a Republican landslide rather than no landslide and the vertical axis the comparable differential logit for a Democratic landslide rather than no landslide. The larger the positive value the greater the probability that a county in the named state delivered either a Republican or a Democratic landslide; the larger the negative value the greater the probability that it did not. (There is a large negative correlation of -0.85 between the two sets of logits.) These differential logits are large in absolute terms. A Massachusetts county was thus much more likely to deliver a Democratic landslide compared to the national average (a logit of 0), for example, while a county in Nebraska was much more likely to deliver a Republican landslide. A clear geographical pattern emerges. The states in the upper left quadrant – a positive logit for Democrat landslide and a negative one for a Republican landslide – are predominantly in either the New England or Pacific divisions; those in the lower right quadrant, especially those furthest to the right, are mainly in the Mountain and High Plains parts of the country.

Model 2: State And County Differentials Vary by Time

Model 1 shows that there is substantial polarization over the period; Model 2 additionally assesses the extent to which the degree of polarization has changed over the period. It allows the state and county differentials to vary by time: instead of identifying a single pattern across all seven elections it explores whether trends by states and counties deviate differentially from the national trend over the period.

In general the variances indicates growing polarization at both scales (Figure 4). Between states (Figure 4a) there is a more than doubling of the variance over the twenty-four years, for both parties: increasingly counties within individual states have either a Republican or a Democratic landslide. There is also a major increase in the variance within states, between counties (Figure 4b), but much more so for Democratic than Republican landslides – at both scales there are growing departures from the national trend. The size of the changing differentials at the state level summarized by these variances can be appreciated from Figure 5 which shows the trends in the logits of a county delivering either a Republican or a Democratic landslide over the period, relative to the national trend, which for the Republican party is upward (Figure 5a) and for the Democratic party is strongly downwards (Figure 5b); only those states which deviate significantly from the national trend are separately identified. For both parties in some states the logits change very little; for most of the New England states, plus some on the west coast, there is a substantial negative logit for a Republican landslide at each election and a corresponding relatively large logit – though in some cases less than zero – for a Democratic landslide. Figure 5a, for example, shows strong upward trends, steeper than the national, in a number of southern states – such as Arkansas, Georgia, Kentucky, Louisiana, Oklahoma, Tennessee, Texas and West Virginia – as well as Kansas and Missouri where the probability of a county returning a Republican landslide increased very substantially. Figure 5b shows much steeper declines in the probability of a Democratic landslide than the national trend in that same group of states, whereas twelve other states – including California, Connecticut, Hawaii, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island and

Vermont on the northeast and west coasts – displayed trends departing from the national in the opposite direction; the probability of a Democratic landslide there either remained relatively constant or increased. Although it is difficult to show graphically a similar process is happening at the county level – the variances show that (particularly for Democratic landsides) counties increasingly deviated from the general trend of the state to which they belong. States deviated from the national trend and counties within states deviated from their state's overall pattern. Polarization, which was very noticeable in 1992 (a logit variance of 14 is very large), became even more marked over time.

Model 3. Introducing Population Characteristics

Models 1 and 2 take no account of differences between counties in their socio-demographic and socio-economic characteristics, focusing only on location within states, the extent of the polarization and how that was changing. Model 3 extends the analysis, therefore, by introducing the scores on the three factors discussed earlier as covariates in the multi-level logistic regressions; it evaluates whether there are geographical variations, by states and by counties within states, in the probability of a county returning a Republican or Democratic landslide over the period, rather than no landslide, once its population characteristics are taken into account. All of the coefficients in the fixed part are highly statistically significant (Table 6). Those for year again show a declining probability of a county returning a Democratic landslide over the seven elections and a, much larger, probability of a Republican landslide. Those for the three factors all show strong relationships between counties with Republican or Democrat landslides rather than no landslide. On the first factor the more Blacks and families in poverty in a county, the greater the probability of a Democratic landslide; the fewer, the greater the probability of a comparable Republican victory. Slightly weaker relationships characterise the other factors: a county is more likely to deliver a Democratic landslide, the greater the percentage of its residents who have degrees and whose households have high incomes (a positive link with Factor 2) and also the more Hispanics who live there (a negative link with Factor 3; per cent Hispanic has a negative loading on the factor – Table 4). These clear relationships indicate that the composition of a county's population is a strong determinant of whether it delivered a landslide to one of the parties, but the large residual variance values for both state and county indicate that population composition represented by the 3 factors is not the sole determinant; there are geographical variations in the landslide patterns over and above population composition.

The relative importance of the three factors as determinants of whether a county delivered a landslide or not and, if so, to which party is shown by the three graphs in Figure 6, which have the same vertical axis so that they are directly comparable The strong relationship with Factor 1 is very clear: counties with high positive scores – with large Black and large poverty-stricken household populations – are very unlikely not to deliver a landslide and almost certain to provide one for the Democrat party's candidate. With Factor 2, on the other hand, the more affluent counties (large percentages of degree holders and high incomes – those with high positive scores) are most likely to have delivered a landslide to neither party: Republican candidates were most likely to win by a landslide in the least affluent counties and Democrats in the most affluent, but the probability of a county not delivering a landslide for either party is more than twice that for a Democratic landslide, which in turn is more than twice that for a Republican landslide. Finally, on Factor 3 those with fewest Hispanics (high positive scores) were least likely to deliver a landslide: counties with many Hispanics were most likely to give the Democratic candidate a resounding majority; those with many non-Hispanic Whites were most likely to do so for the Republicans. (This model assumes the effect of the factors is unchanging over time – essentially the average effect over the period.)

Model 4. Time-Varying Impact of Population Characteristics

Model 4 allows the impact of the three factors on whether a county delivered a majority to either party to differ over time. All but one of the coefficients in the model's fixed part are highly statistically significant (Table 6): the only exception is the link between Factor 3 and Democrat landslides, which because year is centred on 1992, pertain to that year. Importantly, all of the interaction terms between the three factors and year do not include a zero effect in their confidence intervals which indicates that their effects changed over the period.

These changing effects are best appreciated graphically and Figure 7 shows the predicted probabilities of no landslide and either a Republican or a Democratic landslide for the first (1992), median (2004) and final (2016) elections according to a county's scores on the three factors in 2010; in each block of three, the left-hand graph indicates the probability of a county returning no landslide, the central graph is the probability of a Republican landslide, and the right-hand graph is the probability of a Democratic landslide. For Factor 1 (Figure 7a), the curve of the probabilities has a near-normal shape, but with the modal position moving rightwards and lower over time. In 1992, there was a probability close to 0.5 that a county with a very small Black population and with few households in poverty in c.2010 (i.e. with a large negative factor score) would not deliver a landslide to either party; by 2004 that had fallen to c.0.2 and twelve years later to c.0.1. In all three years, on the other hand, the probability of a county with a large positive score on that factor not delivering a landslide was very low. Similarly, at all three elections the probability of a county with a relatively large Black and poor population delivering a Republican landslide was virtually zero (a large positive score on Factor 1: the central graph in Figure 7a). However, for counties at the other end of that continuum – those with few Blacks and poverty-struck households – the probability of a Republican landslide increases substantially, from c.0.5 in 1992 to c.0.9 in 2016. With Democratic landslides, however, the pattern was consistent over the period: those with very few Blacks and poor households were very unlikely to provide one; those with most Blacks and poor households were almost certain to.

On Factor 2 (Figure 7b), the left-hand graph shows that in both 1992 and 2004 there was only a small probability of a county delivering a landslide to neither party according to its share of high income households and degree-holding adults (there is no clear trend over time). That changed in 2016, however, when the probability of a county with few affluent degree-holders (i.e. with a high negative score) failing to produce a landslide fell to c.0.15. This shift is reflected in the other two graphs. In 1992 the most affluent counties were more likely to deliver a Republican landslide than the least affluent; in 2004 and 2016 the situation was not only reversed but also accentuated. The least affluent areas were much more likely to deliver a Republican landslide at the end of the period – probabilities of c.0.1 in 1992 and 0.85 in 2016 (the central graph in Figure 7b); and the most affluent were much more likely to deliver a Democratic landslide in 2016 than 1992 – probabilities of c.0.5 and 0.0 respectively (the right-hand graph).

Finally, the trends for Factor 3 (Figure 7c) similarly indicate increased polarization – greater probabilities of landslides according to local population characteristics. Those with fewest Hispanics and most non-Hispanic Whites (i.e. counties with the highest positive scores in 2010) were more likely to have no landslide than those at the opposite end of the continuum, but the probability at the right-hand extreme more than halved over the seven elections; by 2016 the probability of a county with few Hispanics in 2010 not returning a landslide for either party was c.0.25, compared to c.0.60 in 1992. The right-hand graph in Figure 7c shows that counties with high negative scores (i.e. large Hispanic populations) were much more likely to deliver a Democratic landslide in 2016 than in 1992 (indeed at that first election the probability of such a landslide varied only slightly according to size of the Hispanic population); by contrast, the central graph shows that those with fewest Hispanics and most non-Hispanic Whites (i.e. large positive scores) were much more likely to produce a Republican landslide at the end of the period than at the beginning.

What is the effect of introducing county population characteristics to the models on the separate relative importance of state and county as influences on the geographical patterning of landslides? Figure 4 showed that the variances in the random parts of Model 2 indicated increased polarization both between states and between counties within states over the seven elections. Figure 8 shows the changing variances derived from Model 4, with population characteristic influences held constant. There is relatively little change between the two models in the between-state variances: in Model 2 the variance for both Republican and Democratic landslides increased by c.2.5 times between 1992 and 2016 (Figure 4); in Model 4 it increased by c.2.0 times (Figure 8). But there is a big change between counties within states: Model 4 suggests that once we account for the changing effect of place composition through the factors there is no strong evidence of increasing polarization. In other words, there remains considerable variation between states in the probability of a Republican or Democratic landslide once county population characteristics are taken into account, with that probability changing over time, but that is not also the case between counties within states. The micro-geography of polarization – of a growing number of landslides – between counties is largely a function of their socio-economic and -demographic characteristics. But the macro-geography, at the state scale, is not simply a function of those characteristics: some states are more likely to have counties returning landslides for one of the two parties than others, whatever their counties' population characteristics. It must be stressed, however, that county level polarization remains large (a variance for the logits of around 14 is very sizable) but we have accounted for increasing within-state between-county polarization by the varying trajectories of counties with differing socio-economic characteristics.

Model 5. Time-Specific Trends.

In this final stage we fitted models separately for each year to explore further the changing patterns (the voluminous output is not reported here). The findings are summarised in the nine graphs in Figure 9 which show the probabilities of each outcome – Republican landslide, Democratic landslide, no landslide – according to the values on each factor score, identifying each year separately and with the same vertical axis.

On Factor 1 there is little difference cross the seven elections: the greater the percentage of a county's population that is Black, the greater the percentage unemployed and the greater the percentage in poverty the smaller the probability of a Republican landslide (virtually zero for those counties with the highest positive scores), and the greater the probability of a Democratic landslide – from virtually zero to virtually 1.0 across the full spread of factor scores. Counties with no landslide are clustered around the mean for that factor.

The graphs for the other two factors indicate noticeable changes in the geography over the 24-year period. On factor 2, counties with high negative scores have relatively few people with degrees and relatively low median incomes; in 1992 and 2004 such counties were very unlikely to deliver a Republican landslide (probabilities of less than 0.1) whereas those at the other extreme – with many degree-holders and high-income households – were as likely as not (probabilities of c.0.5). At the later elections, on the other hand, the direction of the trend changes: areas with high negative scores are increasingly unlikely to deliver a Republican landslide whereas those with high positive scores were not. In the late twentieth century affluent counties were quite likely to provide the Republican party with landslide victories; by the second decade of the twenty-first they were not. This switch is mirrored by the probabilities of a Democratic landslide: early in the period the least affluent areas were quite likely to provide the Democratic party's candidate with a landslide victory; by the end of the period, the probability of a county delivering such a landslide was greatest in the most affluent areas.

Finally, on Factor 3 counties dominated by non-Hispanic Whites in 2012 – those with the highest positive scores – were increasingly likely to deliver a landslide to the Republican party whereas those with large Hispanic populations – those with the highest negative scores – were increasingly likely to deliver a Democratic landslide; the probability at the extreme left of the continuum changing from c.0.3 in 1992 to c.0.9 in 2016. As the Hispanic population grew (from around 22 million in 1992 to nearly 57 million in 2015), with 61 per cent voting for Bill Clinton according to the exit polls in 1992 and 65 per cent for Hillary Clinton in 2016, so the areas where they were concentrated, mainly in the southwest, Florida and some of the biggest metropolitan areas (notably New York), were more likely to deliver a landslide victory for the Democratic party.

CONCLUSIONS

The maps of voting at United States' presidential elections from 1992 on provide clear evidence of a growing geographical polarization of the country's electorate, as evidenced by Bishop's chosen indicator of such polarization – counties where one of the two parties' candidates won over the other by more than 20 percentage points, what he termed a landslide. In 1992 more than 63 per cent of all counties were won by less than a landslide; twenty-four years later that percentage had fallen to just 20. The main beneficiary of this change was the Republican party: its candidate won by a landslide in just 19 per cent of the counties in 1992 but in 72 per cent of them in 2016; the Democratic party experienced a decline, however, winning 17 per cent of the counties by a landslide in 1992 but only 7 per cent in 2016. The map became predominantly red as the Republicans came to dominate the election outcomes across much of the country to the west of the Appalachians. But that spatial advantage was not reflected numerically, because many of the counties the Republicans predominated in had relatively few voters: in 2016, 30 per cent of all those who voted lived in Republican landslide counties and a further 30 per cent in Democratic landslide counties. The country became polarized spatially and also numerically.

That polarization has been brought about, according to Bishop (2009), through sorting processes associated with selective migration; households and families with similar characteristics – in their ethnicity, socio-economic status, incomes etc. – have increasingly clustered together in the same areas: spatial segregation has produced political polarization. But what underpins that increased polarization; are the landslides the result only of spatial patterns of segregation, of each party's supporters being increasingly clustered into different places, or are other geographical factors involved – is the polarization greater in some states than others, irrespective of their population composition?

Multi-level modelling has been deployed here to address that question, exploring the geography of the counties that returned landslides for each of the two parties using voting data at seven presidential elections and census data illustrating the main features of their population composition at the end of the period. Within the clear trends over time, this has shown that counties with large Black populations, with high percentages of unemployed and of families living in poverty had high probabilities of delivering landslides for the Democratic party candidates; those with large Hispanic populations also had high, and increasing, probabilities of returning a landslide for the Democratic party. Those patterns were consistent across the seven elections, but the analyses also showed a major switch with regard to one other aspect of local population structure. At the beginning of the period (basically the 1992, 1996 and 2000 elections) counties with relatively large higher-status populations (with high median family incomes and percentages of their adult populations with degrees) were more likely to produce a landslide victory for the Republican than for the Democratic party candidate; at the later elections the reverse was true – the more affluent areas were more likely to deliver a landslide victory for the Democratic candidate and the less affluent areas for the

Republican. This trend was established by the start of the twenty-first century and Trump's victory was an accentuation of it, rather than a clear deviation from existing patterns.

Those findings suggest that compositional factors were crucial determinants of the increasingly polarized electoral geography – who lived where determined whether the Republicans or Democrats won the county by a landslide. But they did not account for all of the variation; there were additional geographies that were more place- than people-specific. The New England states plus many counties on the northeastern seaboard stood apart, for example, with relatively few landslides delivered for either party, as did parts of the Upper Midwest until 2016. A majority of counties in the Mountain and southern states, other than those in the latter region with large Black and/or Hispanic populations, on the other hand, returned Republican landslides at the later elections – probably a reflection of the party's increased attraction to Evangelical Christians, 81 per cent of whom voted for Trump in 2016. (Alabama, Arkansas, Kentucky, Oklahoma and Tennessee have the largest concentrations of Evangelical Protestants according to the Pew Research Centre.[3])

The ideological polarization of the US electorate has been paralleled in recent decades by a spatial polarization – at presidential elections a rapidly-increasing number of counties have returned landslide victories for the Republican party and although the number of counties delivering similar landslides favouring the Democratic party candidates, as many electors live in counties where there have been Democratic landslides as where there has been similar domination by the Republican party. Throughout the period studied here, counties with relatively large Black, poor, unemployed and Hispanic populations have been most likely to deliver landslides for the Democrats while those with large non-White populations have been most likely to favour the Republicans. But alongside those stable patterns there has also been a significant shift: in the 1990s, counties with relatively large percentages of degree-holders and of families with high median incomes were more likely to return Republican than Democratic landslides: two decades later, the reverse was the case, indicating a major switch in the country's electoral geography. But population characteristics did not account for all of the variation in the geography of landslides. Even when those characteristics were taken into account in the multi-level modelling, there remained significant between-state and between-county, within-state variations – variations that changed over time; further evidence of an increasingly complex electoral geography that the modelling undertaken here has explored and illustrated in considerable detail.

REFERENCES

Abrams, S. J. and Fiorina, M. P. 2012. "The Big Sort" that wasn't: a sceptical re-examination. *PS: Political Science and Politics*, 45 (2), 203-210.

Bishop, B. 2009. *The Big Sort: Why the Clustering of Like-Minded America Is Tearing Us Apart*. Boston: First Mariner Books.

Browne, W. J. (2017) *MCMC Estimation in MLwiN v3.00*. Bristol: University of Bristol Centre for Multilevel Modelling.

Bullen, N., Duncan, C. and Jones, K. (1997). 72-2016. *Environment and Planning A*, *29*(4), 585-609.

Campbell, J. E. (2016) *Polarized: Making Sense of a Divided America*. Princeton NJ: Princeton University Press.

[3] http://www.pewforum.org/religious-landscape-study/religious-tradition/evangelical-protestant/

Charlton, C., Rasbash, J., Browne, W. J., Healy, M. and Cameron, B. 2017. *MLwiN Version 3.00*. Bristol: University of Bristol, Centre for Multilevel Modelling

Daley, D. 2016. *Ratf**ked: the True Story Behind the Secret Plan To Steal America's Democracy*. New York: Liveright Books.

Draper, D 2008. Bayesian Multilevel Analysis and MCMC, in Leeuw, J. & Meijer, E. (eds.), *Handbook of Multilevel Analysis*. Berlin: Springer.

Evan, I. S. and Jones, K. 1981. Ratios and Closed Number Systems, in Wrigley, N. and Bennett, R. J. (eds.), *Quantitative Geography: a British View*. London: Routledge and Kegan Paul, 123-134.

Fiorina, M. P. and Abrams, S. J. 2008. Political polarization in the American public. *Annual Review of Political Science*, 11, 563-588.

Glaeser, E. L. and Ward, B. A. 2006. *Myths and Realities of American Political Geography*. Cambridge MA: Harvard Institute of Economic Research, Discussion Paper 2100.

Johnston, R. J., Manley, D. and Jones, K. 2016. Spatial Polarization of Presidential Voting in the United Sates, 1992-2012: the "Big Sort" Revisited. *Annals of the American Association of Geographers*, 106 (5), 1047-1062.

Jones, K. 1991. Specifying and Estimating Multilevel Models for Geographical Research. *Transactions of the Institute of British Geographers*, 16 (2), 148-159

Jones, K. and Subramanian, S. V. 2017a. *Developing Multilevel Models for Analysing Contextuality, Heterogeneity and Change Using MlWin*, *Volume 1*. Bristol: University of Bristol. Available from http://www.bristol.ac.uk/cmm/software/mlwin/mlwin-resources.html

Jones, K. and Subramanian, S. V. 2017b. *Developing Multilevel Models for Analysing Contextuality, Heterogeneity and Change Using MlWin, Volume 2*. Bristol: University of Bristol. Available from http://www.bristol.ac.uk/cmm/software/mlwin/mlwin-resources.html

McGann, A. J., Smith, C. A., Latner, M. and Keena, A. 2016. *Gerrymandering in America: the House of Representatives, the Supreme Court, and the Future of Popular Sovereignty*. Cambridge: Cambridge University Press.

Rasbash, J., Charlton, C., Jones, K. and Pillinger, R. 2017. *Manual Supplement to MlwiN v3.00*. Bristol: University of Bristol, Centre for Multilevel Modelling.

Retherford, R. D. and Choe, M. K. 1993. *Statistical Models for Causal Analysis*. New York: John Wiley & Sons.

Spiegelhalter, D. J., Best, N. G., Carlin, B. P. and van der Linde, A. 2002. Bayesian Measures of Model Complexity and Fit. *Journal of the Royal Statistical Society, Series B,* 64 (3): 583-640

Table 1. The number of landslide counties at each Presidential election, 1992-2016.

Election	No Landslide	Republican	Democratic	Total
1992	1963	588	526	3077
1996	1923	610	544	3077
2000	1457	1428	192	3077
2004	1222	1692	163	3077
2008	1354	1397	326	3077
2012	1091	1716	270	3077
2016	631	2217	229	3077

Table 2. Total number of voters in Landslide and Non-Landslide Counties

Election	Neither	Republican	Democrat	Total .
1992	51,220,295	8,510,223	23,462,140	83,192,568
1996	49,726,147	7,971,081	28,115,946	85,812,724
2000	55,733,983	21,889,521	23,332,700	100,956,204
2004	62,886,776	32,845,280	24,784,729	120,516,785
2008	66,596,774	22,038,784	40,142,371	128,777,929
2012	62,368,779	28,184,145	35,609,789	126,163,713
2016	50,441,178	38,312,901	38,900,702	127,654,781

Table 3. Mean and standard deviation values for Landslide and Non-Landslide counties on various population characteristics

Variable	Neither	Republican	Democrat	Total
Per cent Degree	22.8 (9.5)	16.4 (5.7)	27.6 (14.1)	18.6 (8.4)
Per cent in Poverty	15.5 (7.0)	15.0 (5.5)	19.6 (10.7)	15.4 (6.5)
Median Family Income	46,044 (11,713)	40,421 (7,426)	46,072 (16,849)	41,988 (9,749)
Per cent Unemployed	7.7 (3.0)	6.5 (2.8)	9.1 (4.6)	6.9 (3.1)
Percent aged 65+	14.3 (3.5)	16.8 (4.1)	12.6 (3.1)	16.0 (4.1)
Per cent Black	15.2 (17.7)	5.2 (8.4)	25.0 (27.1)	8.7 (14.3)
Per cent Hispanic	9.6 (14.2)	6.9 (10.5)	18.5 (25.2)	8.3 (13.3)
Per cent Black/Hispanic	24.8 (19.7)	12.2 (13.3)	43.5 (27.8)	17.1 (18.5)
Per cent non-Hispanic White	69.9 (19.8)	84.6 (13.8)	46.5 (25.0)	78.8 (19.5)
Factor 1	0.43 (1.05)	-0.28 (0.70)	1.24 (1.59)	-0.02 (1.00)
Factor 2	0.48 (1.10)	-0.24 (0.75)	0.74 (1.60)	-0.02 (1.00)
Factor 3	-0.19 (1.03)	0.18 (0.80)	-1.10 (1.69)	0.01 (1.00)

Table 4. Loadings from a principal components factor analysis of the county-level population characteristics

Rotated factor	1	2	3
Per cent Degree	-0.14	0.86	-0.05
Per cent in Poverty	0.67	-0.62	-0.30
Median Family Income	-0.24	0.93	0.09
Per cent Unemployed	0.76	-0.31	-0.11
Per cent 65<	-0.48	-0.51	0.39
Per cent Black	0.85	-0.05	-0.10
Per cent Hispanic	0.01	0.02	-0.96
Per cent Non-Hispanic White	-0.71	-0.01	0.78

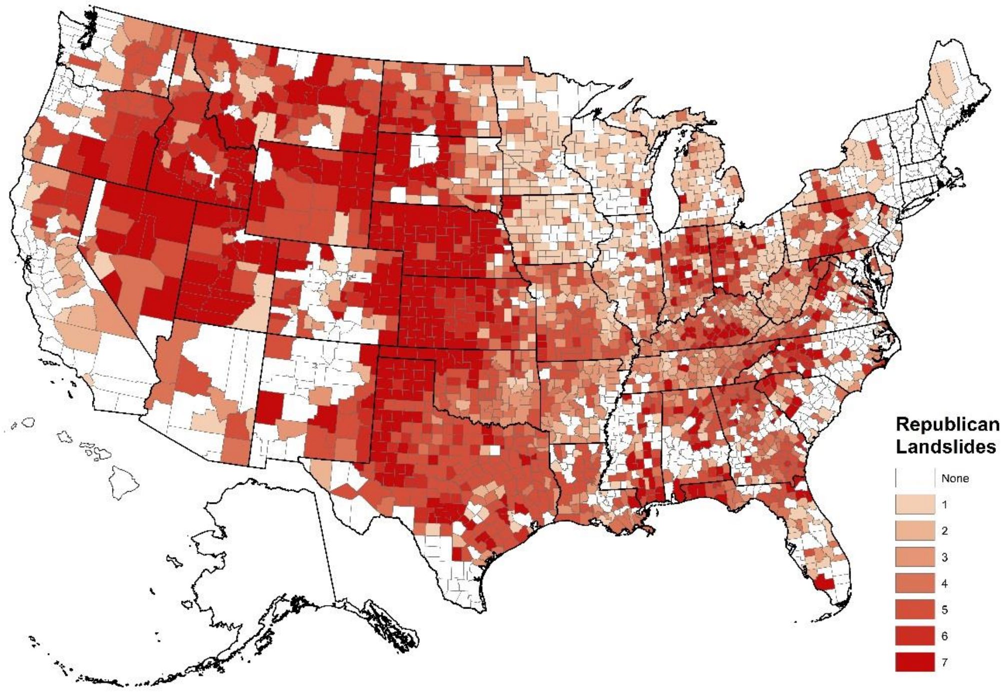
Table 5. The results of fitting Models 1 and 2, showing the coefficients and their credible intervals (CIs) for the fixed part and the variances with their credible intervals for the random part

Model		1			2	
	2.5%CI	Coeff.	97.5%CI	2.5%CI	Coeff.	97.5%CI
Fixed part						
Constant: Republican	-5.80	-4.70	-3.65	-6.22	-5.02	-3.90
Constant: Democrat	-4.80	-3.91	-3.04	-6.07	-4.94	-3.86
Year: Republican	0.23	0.24	0.25	0.19	0.26	0.31
Year: Democrat	-0.09	-0.08	-0.07	-0.33	-0.25	-0.18
Random part						
State level						
Variance: Republican	7.93	13.15	21.20	8.33	14.18	23.34
Variance: Democrat	4.76	8.10	13.16	6.54	11.38	18.78
Variance: Year-Republican				0.02	0.04	0.06
Variance: Year-Democrat				0.03	0.05	0.08
County level						
Variance: Republican	8.90	9.86	10.90	11.42	13.41	15.63
Variance: Democrat	11.10	12.95	15.02	18.17	22.53	27.53
Variance: Year-Republican				0.03	0.03	0.04
Variance: Year-Democrat				0.05	0.06	0.08
DIC	19573.773			16095.825		

Table 6. The results of fitting Models 3 and 4, showing the coefficients and their credible intervals (CIs) for the fixed part and the variances with their credible intervals for the random part

Model		3			4	
	2.5%CI	Coeff.	97.5%CI	2.5%CI	Coeff.	97.5%CI
Fixed part						
Constant: Republican	-8.15	-6.45	-4.85	-6.79	-5.47	-4.24
Constant: Democrat	-7.21	-5.87	-4.57	-5.59	-4.42	-3.29
Year: Republican	0.26	0.30	0.36	0.21	0.26	0.31
Year: Democrat	-0.13	-0.05	0.01	-0.32	-0.25	-0.19
Factor 1: Republican	-4.06	-3.74	-3.44	-2.76	-2.40	-2.05
Factor 1: Democrat	2.93	3.28	3.66	2.06	2.42	2.81
Factor 2: Republican	-1.24	-1.04	-0.84	0.76	0.97	1.17
Factor 2: Democrat	0.33	0.62	0.92	-1.43	-1.15	-0.87
Factor 3: Republican	0.67	0.89	1.13	-0.61	-0.34	-0.08
Factor 3: Democrat	-1.53	-1.23	-0.94	-0.19	-0.50	0.11
Year.F1: Republican				-0.12	-0.10	-0.08
Year.F1: Democrat				0.08	0.11	0.14
Year.F2: Republican				-0.14	-0.13	-0.12
Year.F2: Democrat				0.13	0.15	0.17
Year.F3: Republican				0.07	0.08	0.10
Year.F3: Democrat				-0.12	-0.10	-0.08
Random part						
State level						
Variance: Republican	18.02	30.56	49.86	10.34	17.58	28.68
Variance: Democrat	9.82	13.63	26.27	7.92	13.36	21.58
Variance: Year-Republican	0.02	0.02	0.04	0.02	0.03	0.04
Variance: Year-Democrat	0.03	0.04	0.07	0.01	0.03	0.05
County level						
Variance: Republican	18.20	21.18	24.49	8.96	10.54	12.33
Variance: Democrat	22.43	27.71	33.88	14.37	17.81	21.93
Variance: Year-Republican	0.02	0.03	0.03	0.01	0.01	0.02
Variance: Year-Democrat	0.04	0.05	0.06	0.02	0.02	0.03
DIC	15917.760			15566.209		

Figure 1. Counties according to the number of landslides delivered to the Republican and Democratic parties across the seven presidential elections 1992-2016.



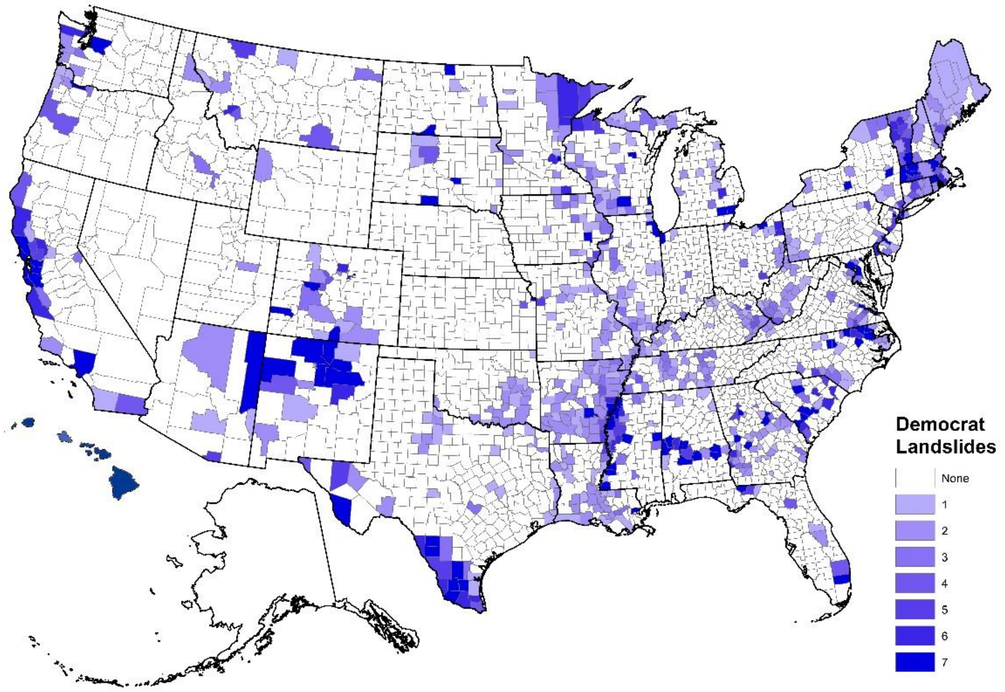


Figure 2. The changing probability of a Republican landslide, a Democratic landslide, or no landslide in the mean county in the mean state according to Model 1.

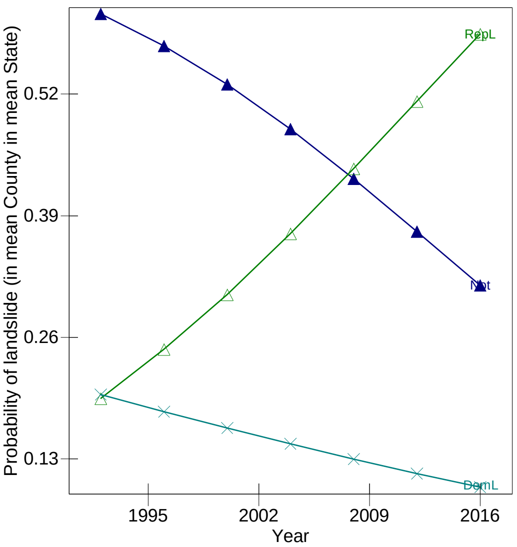


Figure 3. The differential logits for a county returning a Republican and a Democratic landslide, as against no landslide, by state, according to Model 1.

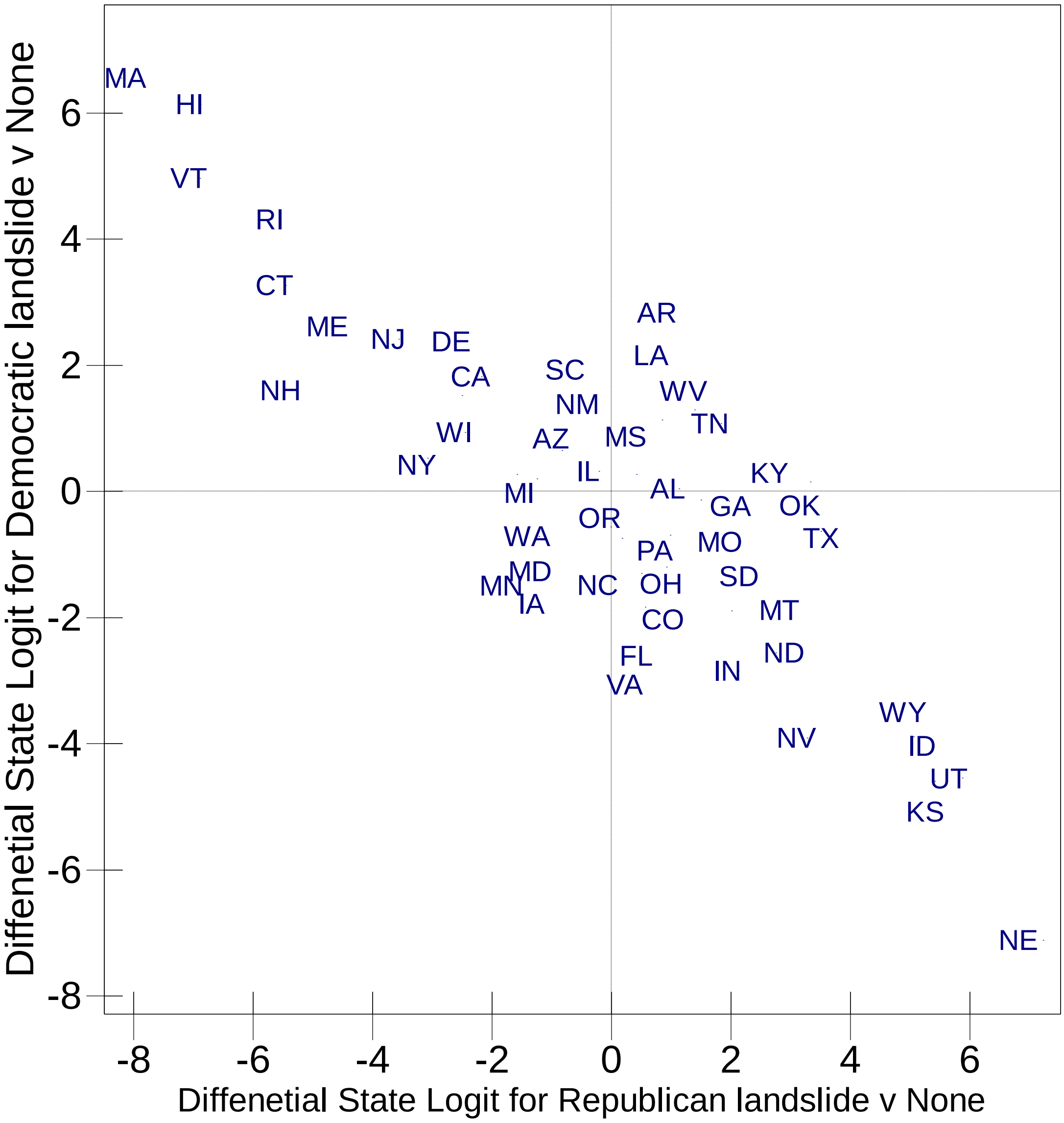


Figure 4. The changing variances for counties returning a Republican or a Democratic landslide by (a) state (the left-hand graph) and (b) by county within state (the right-hand graph) according to Model 2.

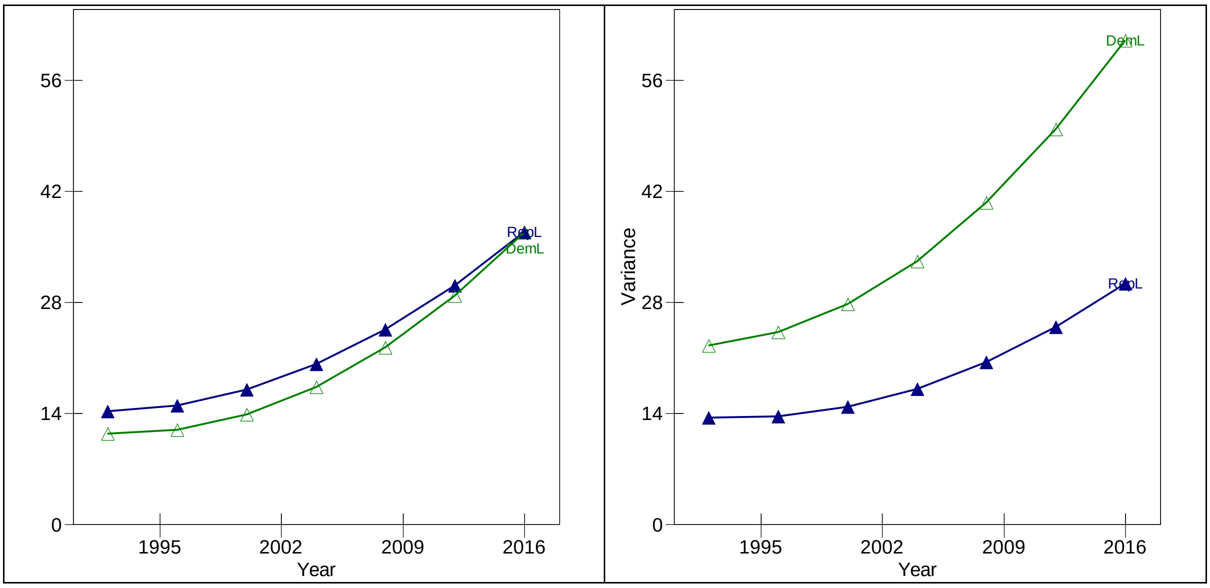


Figure 5a. The changing logit of a county in a state returning a Republican landslide according to Model 2: only those states with a significantly different slope from the national trend are shown.

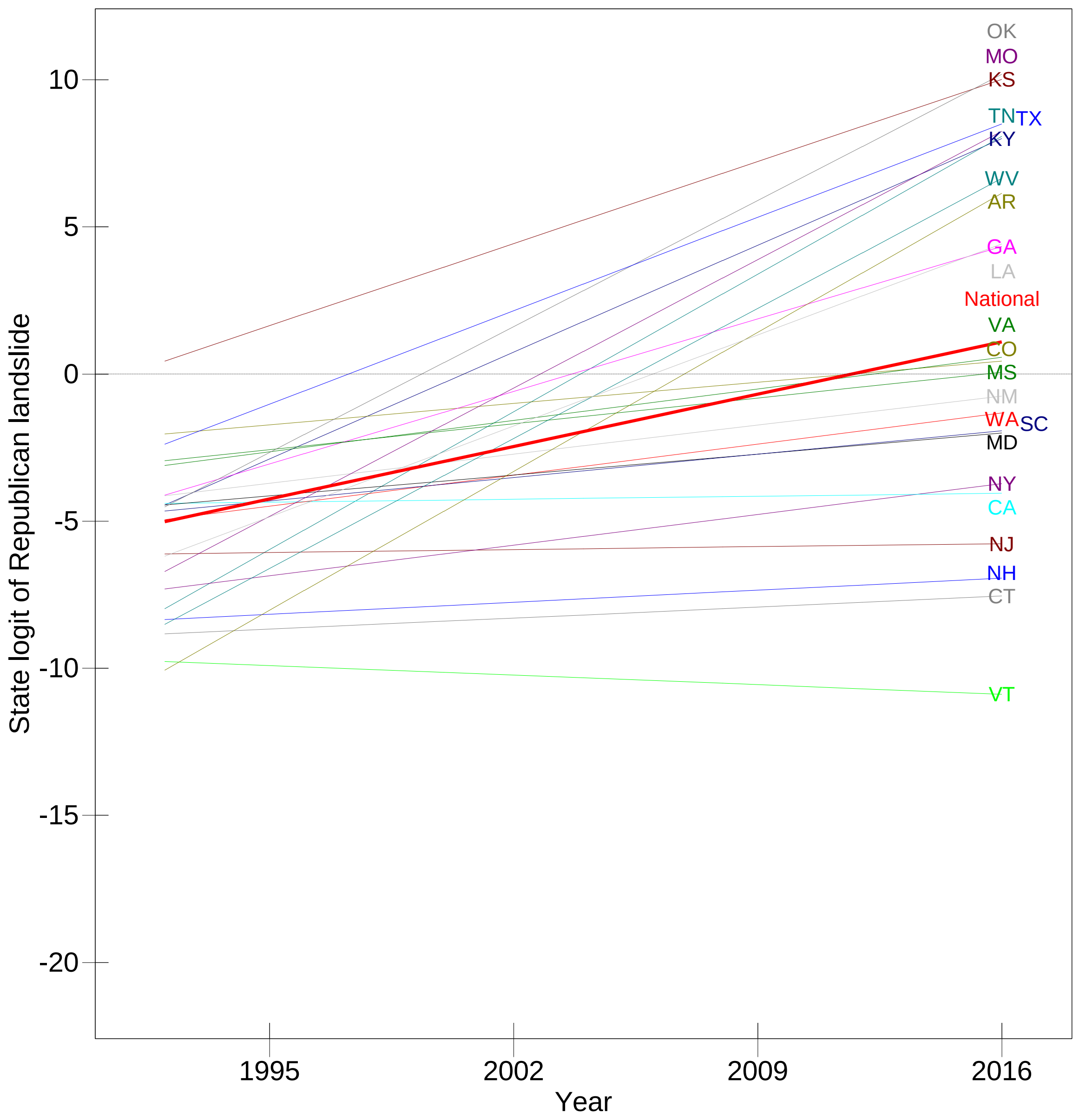


Figure 5b. The changing logit of a county in a state returning a Democratic landslide according to Model 2: only those states with a significantly different slope from the national trend are shown.

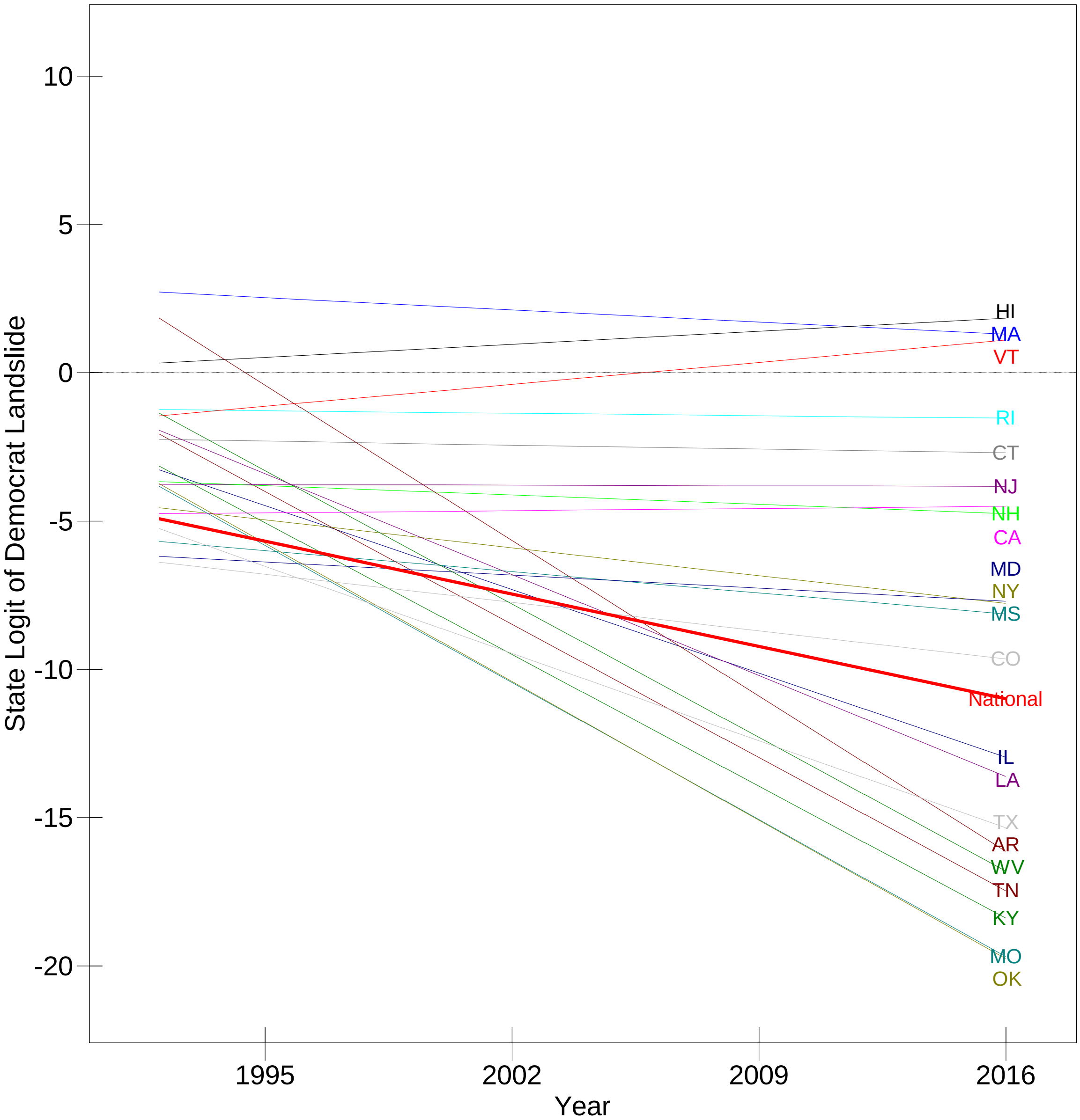


Figure 6. The probability of a county returning a Republican landslide, a Democratic landslide or no landslide according to their values on the three population characteristic factors, according to Model 3.

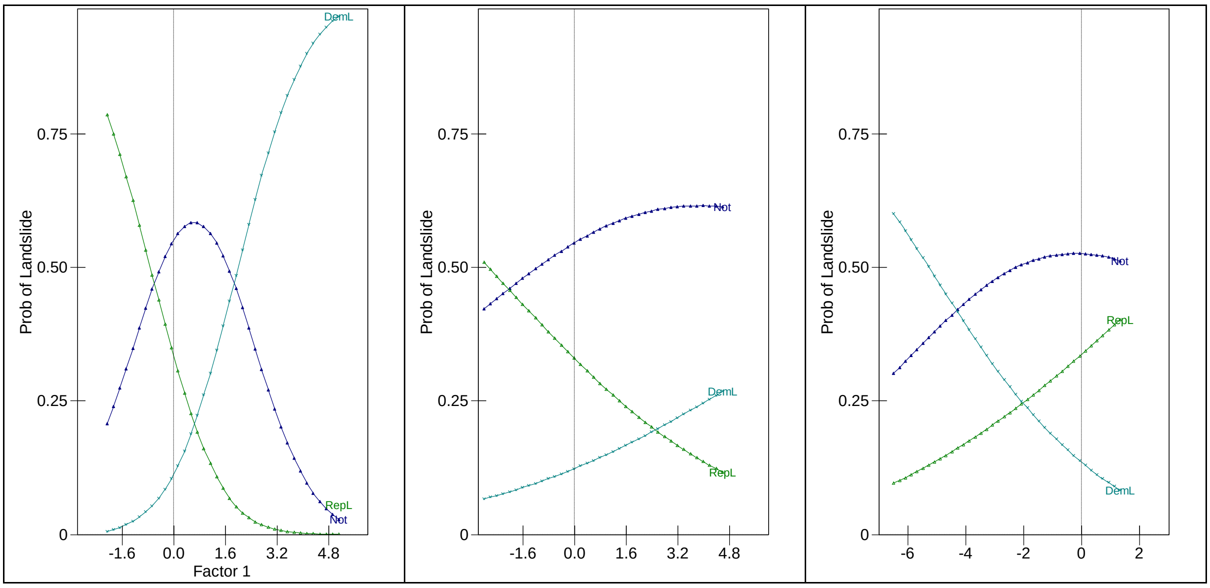
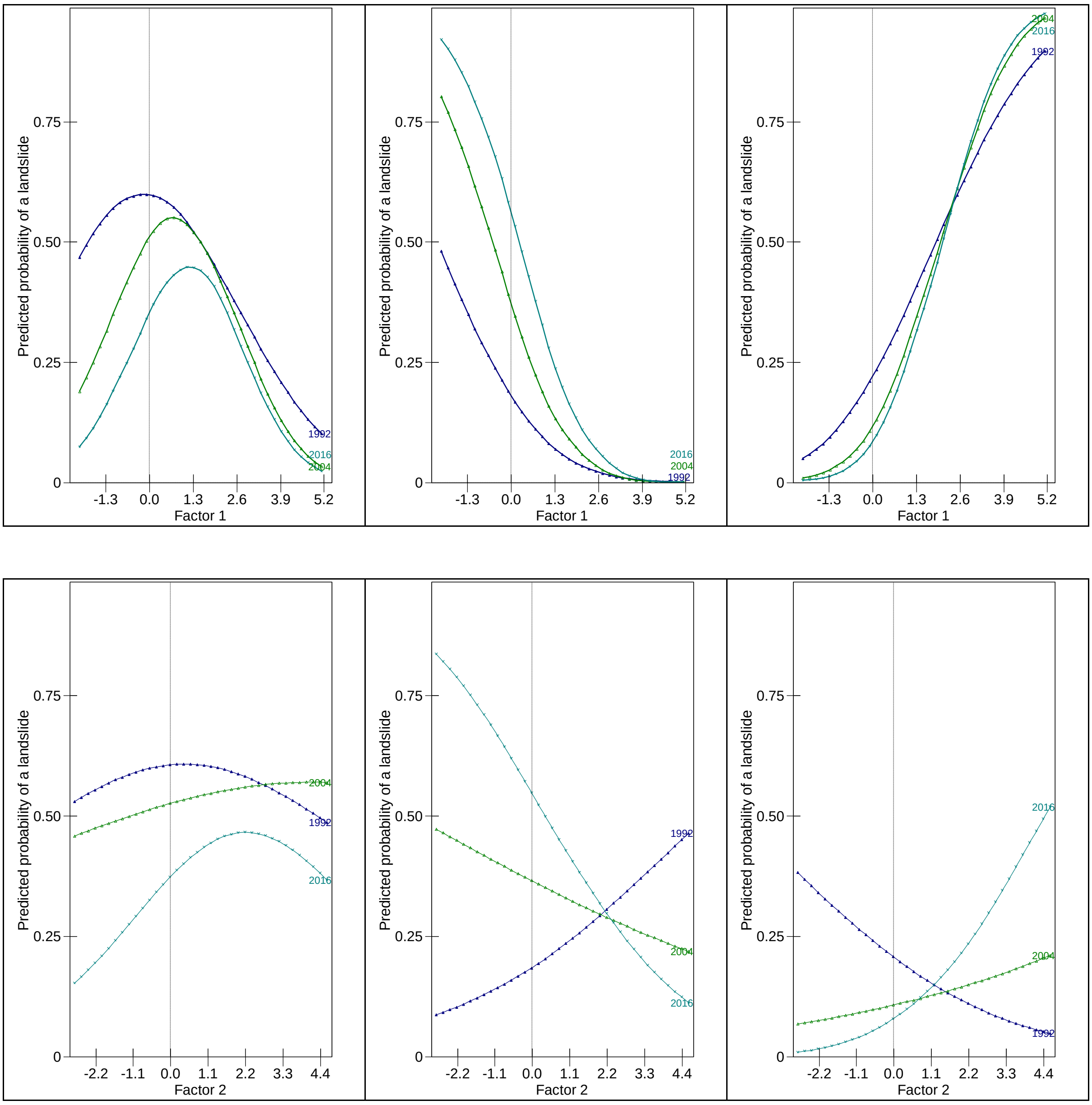


Figure 7. The probabilities of a county returning no landslide (the left-hand column), a Republican landslide (the central column) or a Democratic landslide (the left-hand column) in 1992, 2004 and 2016, according to their values on the three population characteristic factors, according to Model 4.



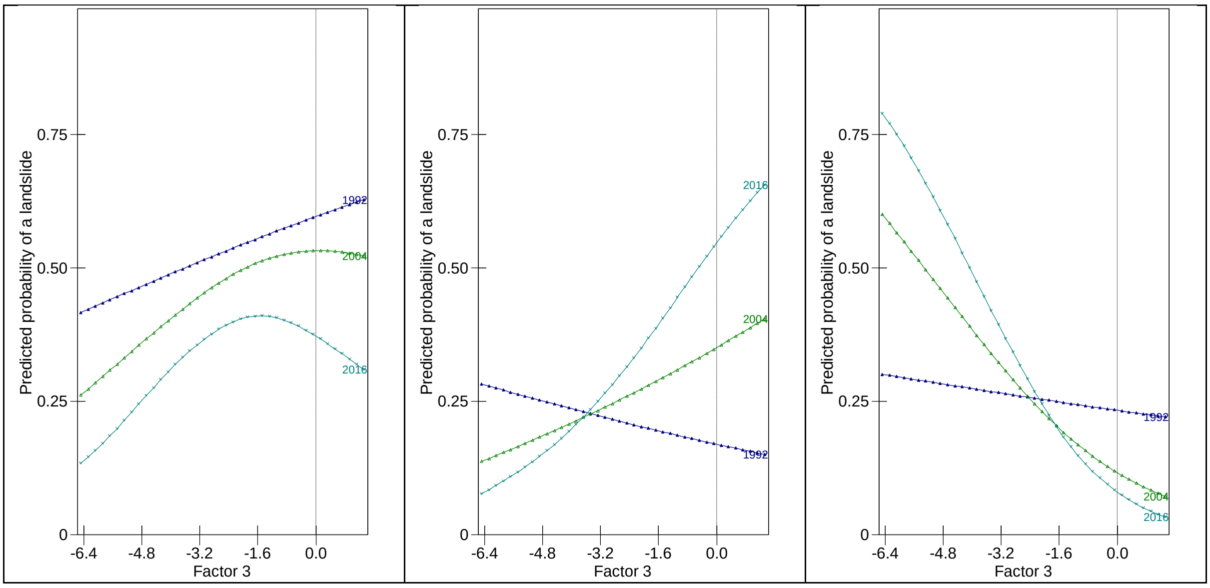

Predicted probability of a landslide
0.75
0.50
0.25
0
-6.4
-4.8
-3.2
-1.6
0.0
Factor 3
1992
2004
2016

Figure 8. The changing variances for counties returning a Republican or a Democratic landslide by (a) state (the left-hand graph) and (b) by county within state (the right-hand graph), with their values of the population characteristic factors held constant, according to Model 4.

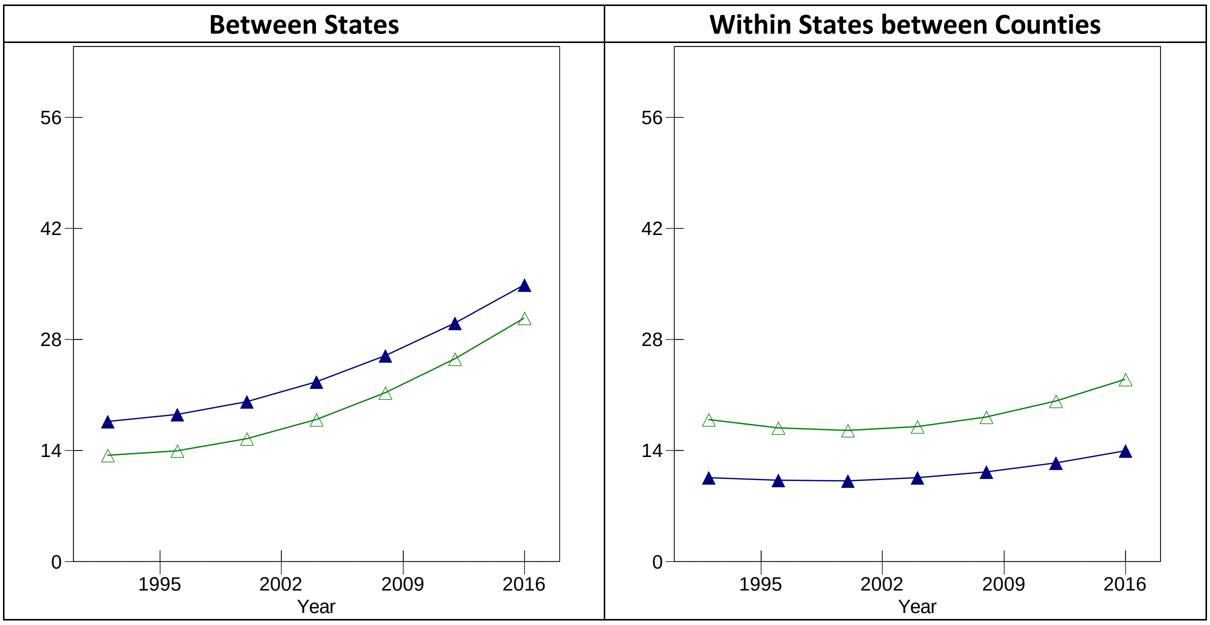
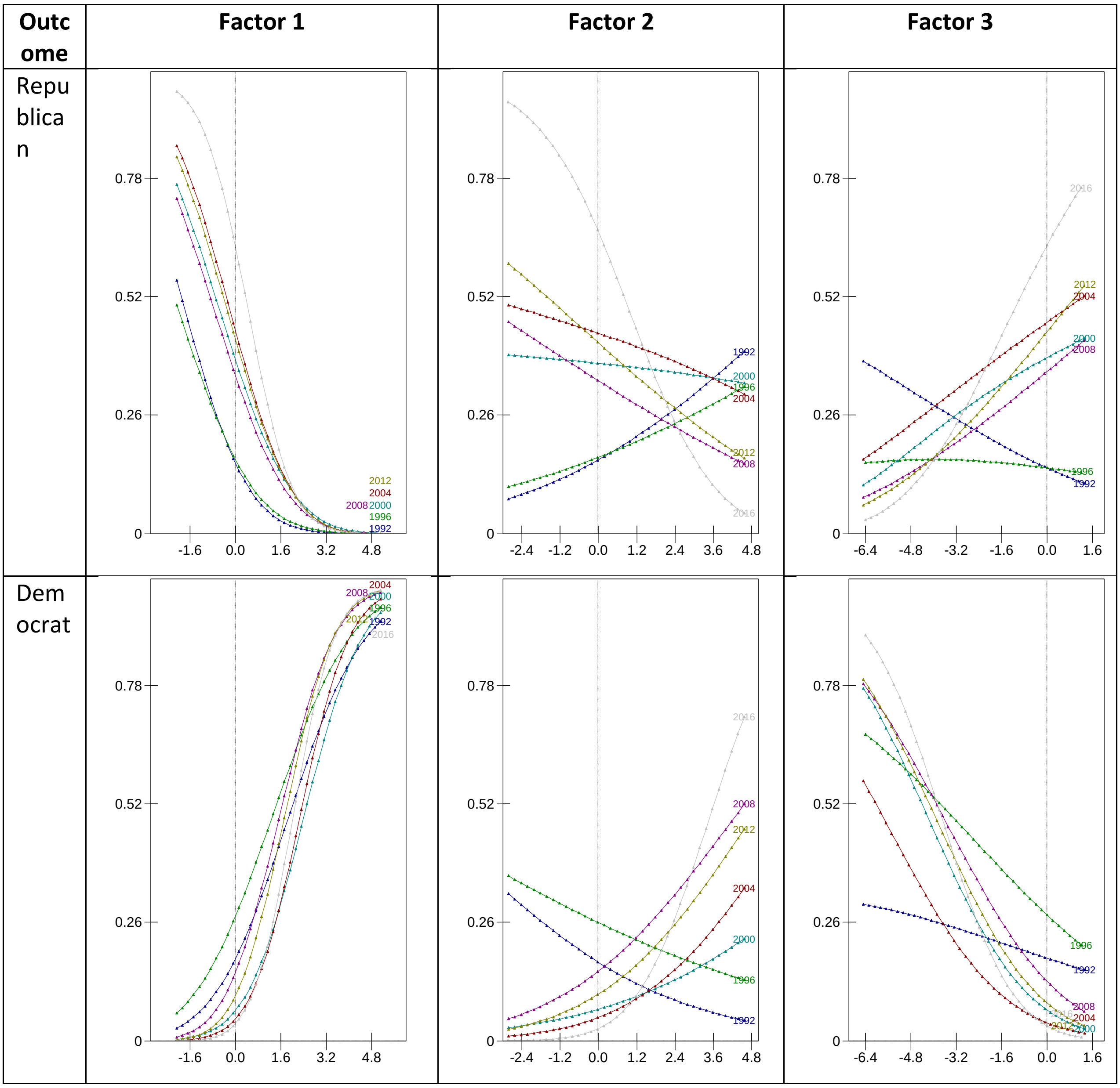
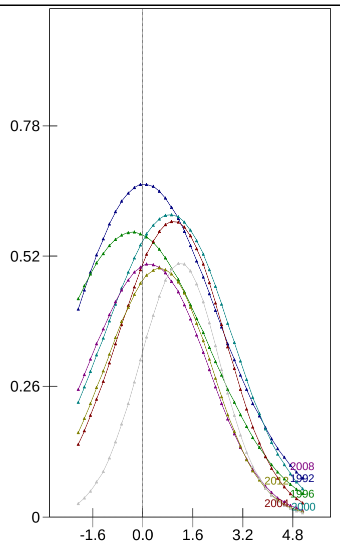
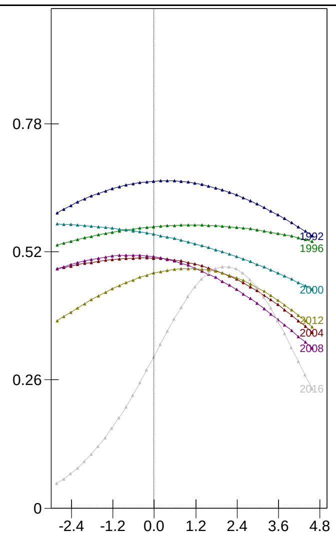
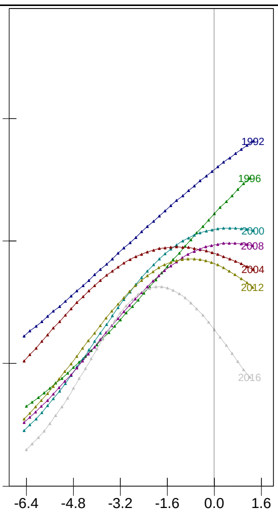


Figure 9. The probabilities of a county returning a Republican landslide, a Democratic landslide, or no landslide in each year, according to their values on the population characteristic factors, according to Model 5.



None			

0.78
0.52
0.26
0
-1.6
0.0
1.6
3.2
4.8
2008
1992
2012
1996
2004
2000

0.78
0.52
0.26
0
-2.4
-1.2
0.0
1.2
2.4
3.6
4.8
1992
1996
2000
2012
2004
2008
2016

0.78
0.52
0.26
0
-6.4
-4.8
-3.2
-1.6
0.0
1.6
1992
1996
2000
2008
2004
2012
2016

APPENDIX: MODEL SPECIFICATIONS AND ESTIMATION

This appendix sets out the details of the models applied and briefly considers how they estimated as Bayesian models.

Model 1: the Multilevel Multinomial Model with State and County Departures from a General Trend

$$y_{ijk}^{N}, y_{ijk}^{R}, y_{ijk}^{D} \sim Multinomial\ (\pi_{ijk}^{N}, \pi_{ijk}^{R}, \pi_{ijk}^{D})$$

$$Logit(\pi_{ijk}^{R}) = Loge(\pi_{ijk}^{R}/\pi_{ijk}^{N}) = \beta_0 + \beta_2 (Year - 1992)_{ijk} + v_{0k} + u_{0jk}$$
$$Logit(\pi_{ijk}^{D}) = Loge(\pi_{ijk}^{D}/\pi_{ijk}^{N}) = \beta_1 + \beta_3 (Year - 1992)_{ijk} + v_{1k} + u_{1jk}$$

$$\begin{bmatrix} v_{0k} \\ v_{1k} \end{bmatrix} \sim N(0, \begin{bmatrix} \sigma_{vo}^2 & \\ \sigma_{v0v1} & \sigma_{v1}^2 \end{bmatrix})$$

$$\begin{bmatrix} u_{0jk} \\ u_{1jk} \end{bmatrix} \sim N(0, \begin{bmatrix} \sigma_{uo}^2 & \\ \sigma_{u0u1} & \sigma_{u1}^2 \end{bmatrix})$$

$$Var\ (y_{ijk}|\pi_{ijk}) = \begin{bmatrix} \pi_{ijk}^{N}(1-\pi_{ijk}^{N}) & & \\ -\pi_{ijk}^{N}\pi_{ijk}^{R} & \pi_{ijk}^{R}(1-\pi_{ijk}^{R}) & \\ -\pi_{ijk}^{N}\pi_{ijk}^{D} & -\pi_{ijk}^{R}\pi_{ijk}^{D} & \pi_{ijk}^{D}(1-\pi_{ijk}^{D}) \end{bmatrix}$$

The observed response variable (y_{ijk}) is a set of three outcomes with either a 1 or 0 representing whether a county was not a landslide, a Republican landslide or a Democrat landside signified by the superscript N, R and D. This is a closed-number set (Evans and Jones 1981) as a county can only be in one category and we consequently we model this as a multinomial distribution where we are interested in the underlying probability of the outcome (π_{ijk}) which must sum to 1 across the three potential responses. The subscripts (*ijk*) indicate that we are dealing with a multilevel structure with repeated measures for years (at level 1) nested within counties at level 2 and States at level 3. In practice (to avoid impossible predictions and achieve more plausible model assumptions), we choose the No landslide outcome as the referent group and model the log-odds (the logits) of the other two outcomes in relation to that.[4]

This results in two wings of an equation with the outcome being the log odds of a Republican landslide compared to No landslide in one wing and the log-odds of being a Democratic landslide compared to No Landslide in the other. In the fixed part of this multilevel model (Jones, 1991), there is one predictor in both wings – the year the election took place.[5] As this variable is modelled as a difference from 1992 (the earliest year included in the analysis), the terms associated with the β_0 and β_1 give the log-odds of each outcome in that year. The two slope terms (β_2 and β_3) give the change in the log-odds for a unit change in the variable year. In each of the wings there is therefore a general overall trend summarised by an intercept and an overall slope, ($\beta_0$and β_2 for the logit of Republican landslides). Additionally, in each wing there are allowed-to-vary departures at both the state and the county level (the so- called random

---

[4] It seems natural to use no landslide as a base but it is worth stressing that is possible to drive all the terms of both alternative specifications (averages and variances) without refitting the models. Thus $\beta^{(D|R)} = \beta^{(D|N)} - \beta^{(N|R)}$.

[5] Given the complexities that come later we have simply specified an overall trend across the 1992-2016 period on the log-odds scale.

intercepts), so that $v_0$is the state logit departure from the general line for Republican landslides, while $u_0$is the county logit departure from the state, again for Republicans. If the former is positive there is a greater chance of a Republican landslide in that state than nationally; if the latter is negative then that county has a lower chance of such a landslide in comparison to the state it is in.

These logit departures are assumed in the random part of the to be normally distributed and are summarised by variance terms at the state and county level (the loge transformation of the odds making the normality assumption more plausible). Thus, the variance σ_{v0}^2 summarises the state differentials for Republican landslides and if this term is zero there is no differences in this outcome at this level. Similarly. σ_{u1}^2 summarises the within state, between county differences for Democratic landslides. A large value for these variances means there is a strong geography in the outcome – where you are matters in terms of landslides. The off-diagonal covariances terms (once standardised) summarize the degree of correlation at a particular level for the two types of departure so that σ_{v1v2} measures the association between the logit departures for Republican and Democratic landslides at the state level. (This is not a forgone conclusion as the inbuilt correlation is not at this level.) The final part of the equation specifies a variance covariance of an exact multinomial distribution at lowest level for the residual variation after taking account of the terms in the fixed part of the model and the higher-level random terms. The variances in this matrix are the underlying probability of an outcome multiplied by its complement while the covariances reflect the inbuilt negative correlation between this closed number set.

More Complex Models

Subsequent models build on the above and can be more complex by adding terms to the fixed part and to the random part. The second model builds on the first in allowing the differential effects at the State and County levels to change with year. It answers the question of whether state and/or county geography is becoming more important over time – i.e. the extent and nature of the polarization around the overall trend and gives us the changing between county and state variation that needs to be explained. Model three additionally includes the three factors in the fixed part while model four additionally includes year by factor interactions to assess the changing effect of factors on the outcomes.

Model 4, the most complex we fitted is specified as follows:

$$y_{ijk}^N, y_{ijk}^R, y_{ijk}^D \sim Multinomial\ (\pi_{ijk}^N, \pi_{ijk}^R, \pi_{ijk}^D)$$

$$Logit(\pi_{ijk}^R) = \beta_0 + \beta_2(Yr-92) + \beta_4 F1 + \beta_6 F1(Yr-92) + \cdots + \beta_{14} F3(Yr-92) + \\ v_{0k} + v_{2k}(Yr-92) + u_{0jk} + u_{2jk}(Yr-92) +$$

$$Logit(\pi_{ijk}^D) = \beta_1 + \beta_3(Yr-92) + \beta_5 F1 + \beta_7 F1(Yr-92) + \cdots + \beta_{15} F3(Yr-92) + \\ v_{1k} + v_{3k}(Yr-92) + u_{1jk} + u_{3jk}(Yr-92)$$

$$\begin{bmatrix} v_{0k} \\ v_{1k} \\ v_{2k} \\ v_{3k} \end{bmatrix} \sim N(0, \begin{bmatrix} \sigma_{vo}^2 & & & \\ \sigma_{vov1} & \sigma_{v1}^2 & & \\ \sigma_{vov2} & \sigma_{v1v2} & \sigma_{v2}^2 & \\ \sigma_{vov3} & \sigma_{v1v3} & \sigma_{v2v3} & \sigma_{v3}^2 \end{bmatrix})$$

$$\begin{bmatrix} u_{0jk} \\ u_{1jk} \\ u_{2jk} \\ u_{3jk} \end{bmatrix} \sim N(0, \begin{bmatrix} \sigma^2_{uo} & & & \\ \sigma_{uou1} & \sigma^2_{u1} & & \\ \sigma_{uou2} & \sigma_{u1u2} & \sigma^2_{u2} & \\ \sigma_{uou3} & \sigma_{u1u3} & \sigma_{u2u3} & \sigma^2_{u3} \end{bmatrix})$$

$$Var\left(y_{ijk}|\pi_{ijk}\right) = \begin{bmatrix} \pi^N_{ijk}\left(1-\pi^N_{ijk}\right) & & \\ -\pi^N_{ijk}\pi^R_{ijk} & \pi^R_{ijk}\left(1-\pi^R_{ijk}\right) & \\ -\pi^N_{ijk}\pi^D_{ijk} & -\pi^R_{ijk}\pi^D_{ijk} & \pi^D_{ijk}\left(1-\pi^D_{ijk}\right) \end{bmatrix}$$

The basic form of the model remains the same with a three-level multinomial structure (to make the equations more compact the subscripts are dropped where they are obvious), however the two wings for the logits are considerably expanded. Each wing now has four observed variables: the year centred around 1992 and the three factors scores (F1, F2, F3) centred around their grand mean; and there are interactions between each factor and year. Because of the centering β_0 is the logit of a Republican landslide in 1992 in a county which is average on all three factors. The slope term β_2 gives the change in this logit for an increase of a year in an average place while the slope β_4 gives the main effect for factor 1 in 1992 and there are similar slope terms for factors two and three. The rest of the fixed part of the model is the slopes for the interactions between factor and year so that β_{14}respresents the change in the Republican logit for a combination of year and factor 3. The same elaboration is performed in the Democrat wing of the model. Both wings have additional sets of random terms at both the state and county level. Thus, $v_{0k}$is the Republican logit differential intercept at the state level and gives whether the state is differentially high or low in 1992 once account is taken of population characteristics through the inclusion of the three factors. In a similar fashion, $v_{1k}$is the Republican logit differential slope associated with year; a positive value indicating that the state has a steeper differential rise compared to the overall average trend after taking account of the potential changing effect of the factors.

In total, there are four random differentials at the state and county representing differential intercepts and slopes for Republican and Democratic landslides. These differentials are again summarised in variance-covariance terms at each level. Thus σ^2_{v0} summarises the state differentials for Republican landslides in 1992 and if this term is zero there are no differences in this outcome at the state level. The variance term σ^2_{v2} summarises the state differential slopes and if this term is zero the states follow the national trend and do not depart from it. The covariance terms are important with for example σ_{v0v2} giving the association between the differential logit for Republicans at the state level in 1992 with the differential slope over the period. These terms combined in a quadratic equation to define a variance function; thus (Bullen et al, 1997) for the logits for Republicans at the state level it is:

$$Var(v_{0k} + v_{2k}(Yr-92)) = \sigma^2_{vo} + 2\sigma_{v0v2}(Yr-92) + \sigma^2_{v2}(Yr-92)^2$$

If the covariance term is positive there is evidence of increasing polarization over time.

Although these models are based on the logits it is possible to derive estimated probabilities. This if often convenient for interpretation as the logits can mislead even about the sign of the relation (Retherford and Choe (1993).

Estimation

The models are estimated as Full Bayesian models using the MLwiN software with Markov-Chain Monte-Carlo procedures (Jones and Subramanian,2017; Charlton et al, 2017). The default priors (Browne, 2017) are used to impart as little information as possible to the estimates. There are several reasons for doing this: quasi-likelihood procedures are known to underestimate the higher-level variances; Full Bayes procedures take account of uncertainty in all parameters both fixed and random simultaneously; asymptotic normality is not assumed for the estimates of the variance parameters and the derived credible intervals (Bayesian confidence intervals) can be asymmetric. Finally, these procedures allow the calculation of a Bayesian Deviance Information Criterion (Spiegelhalter, 2002) which is a complexity-penalized badness-of-fit measure where complexity is estimated and takes account of the number of parameters in the fixed and random parts of the model. It is now common practice that a reduction of 10 or greater when two models are compared reflects a substantial improvement in the goodness of fit. We followed Draper's (2008) good practice guidelines in determining when the simulations chains have been run for long enough. We also used the MLwiN software to calculate cluster-specific and population average probability predictions from the logits (Rasbash et al., 2017); the latter take account of the random effects.